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Probability of Precipitation using Updateable Model Output Statistics

By

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1. Introduction

In this section, the background to Updateable Model Output Statistics (MOS) is introduced, together with a brief introduction to the Probability of Precipitation (PoP) model. Section 2 deals with the development and processing of the PoP model, while Section 3 describes the verification and Section 4 the results.

1.1 Origins of MOS

The name 'Model Output Statistics' (MOS) became widely known after the paper by H R Glahn and D A Lowry (1972). They used statistical modelling to derive forecasts of weather parameters at particular sites, from point values of the fields of the American Limited Fine Mesh (LFM) Numerical Weather Prediction (NWP) model. These point values were taken from a vertical profile (ascent) above the station position. The values themselves were often representative of deep layers of the atmosphere such as heights and thickness', rather than finer detail such as temperatures within the boundary layer. This acknowledged the fact that these gross atmospheric parameters are better modelled by the NWP process and are less susceptible to algorithmic changes to the NWP model.

Statistical modelling requires the creation of an archive of past data of both the NWP data and observations of the weather parameter. From their archive, Glahn and Lowry derived statistical models that allowed inferences about future observations to be made from knowledge of the NWP data only.

1.2 NWP Model Enhancements and MOS

Statistical models, which are developed from archives from a 'stable' NWP model, can suddenly develop errors when there is a change to the numerical model. MOS models have been developed by many national meteorological services. However, the biggest constraint is gathering a sufficiently long archive with a sufficiently representative range of weather variation, while the numerical model is stable.

When there is a change to the numerical model, systematic errors can appear in the MOS forecasts. Therefore a re-computation of the statistical models is required, using only a short period of data that behaves as the current version of the NWP model. That short length of data itself may be unrepresentative of the true climate because of the particular weather sequence that occurred during the period of the stable NWP model. A technique is described in this report that uses an updateable or recursive formulation of the MOS model. At the end of each month the new data are gathered from the NWP model and observations, and are sorted to be valid at the same time. These data are now added to the existing data and then incorporated into the statistical model. Then every regression equation for the following month is re-computed.

1.3 Introduction to Probability of Precipitation (PoP)

There are three new Probability of Precipitation (PoP) products (see Table 1), from the UK Updateable Model Output Statistics Scheme. (Lists of the stations used in the PoP products can be found in Appendix B). The intention is to give an initial estimate of the probability to the forecaster who needs to predict whether it will precipitate or not, at a given station, and in a given time period. Probabilities are a good way of passing information, only if they are well specified. These PoP forecasts are site specific and time specific. Such forecasts refer to a particular station and particular 6 or 12 hour period in the forecast. The MOS PoP model uses updateable (or recursive) regression methods to provide information about precipitation events. In contrast to the Operational MOS temperature products, it does not provide an estimate of

the weather parameter involved; rather it forecasts information about the 'uncertainty' of a precipitation event.

	GLOBAL UK	GLOBAL EUROPE	LAM UK
AREA	UK and Ireland	Europe (not UK, Ire.)	UK and Ireland
MODEL	Global	Global	Limited Area
NO. OF STATIONS	140	150	140
PERIOD/HR'S	12	12	6
LATEST FORECAST	T+144	T+144	T+36

TABLE 1 : Definition of the three PoP products

For each station and forecast time, a percentage is given to forecast the likelihood of precipitation, at that station in a given time period. In the PoP products, a precipitation event is defined as 'any precipitation greater than 0.4mm, collected in a specified time period at a given station.' This 0.4mm criterion was chosen with the help of the Verification Working Group in the CFO, and could be changed if the Working Group so desired. The specified time period depends on the PoP product. This is the previous six hours from the validity time for the PoP product from the Limited Area model, or the six hours either side of the validity time for the PoP products from the Global model. The PoP forecast is assigned in 5% categories, with the lowest probability being ' <5% ' and the highest being ' >95% '. If for example, the LAM PoP forecast at a certain station is 20%, this means that, on average over a number of such forecasts, it should rain on 2 occasions out of 10, for that station over the appropriate 6 hour period.

2. Development of the POP Model

2.1 Gathering Data

The PoP model uses data from the observed 6 hour accumulations from the International Climatological dataset, and NWP forecast data from the MOS archive. The International Climatological dataset is a monthly archive of all European stations, maintained by the Met. Database Group in the Information Technology Branch. The MOS archive contains data from 1984 to present, although only Unified Model data from October 1991 onwards has been used in the current PoP model. In the PoP model, the NWP data is interpolated to each station position, to obtain the vertical profile (or ascent) of data.

2.2 NWP Parameters used in the Model

Most MOS models work on the same principle: by matching the observations and forecast parameters, a statistical relationship is formed. It is possible to find a subset of NWP parameters that 'best' forecast the observed precipitation events by means of regression equations. A number of NWP parameter subsets were tested. These parameters included pressure, temperatures and dew points, temperature and dew point advections, wind speed, vertical wind shear, horizontal divergences and vorticities and model rainfall forecast accumulations and rates.

The MOS temperature products forecast maximum and minimum temperatures. These products use parameters from the first and fourth levels, as well as some 'surface' terms. For

the PoP model, levels 1, 4 and 7 (sigma values of 0.997, 0.870 and 0.590, respectively) are used, as they span a good reasonable range of the atmosphere where rainfall evolves. The levels themselves are far enough apart from each other to give extra information about the atmosphere, and to be sufficiently independent of each other. An earlier analysis showed that levels 1, 2 and 3 are too dependent on each other to use together. Level 4 is at the top of the boundary layer, but is still affected by major topographic differences. For similar reasons, e.g. high level cloud, level 7 is also used in the PoP model. After a statistical investigation, the following parameter set was chosen to represent all stations and times.

Dew point (Levels (1,4,7))
Wind Speed (Levels (1,4,7))
Divergence (Levels (1,4,7))
Vorticity (Levels (1,4,7))
Mean Sea Level Pressure
Accumulated Dynamic Rain (indicator variable)
Accumulated Convective Rain (indicator variable)
Wind Directions in 8 sectors

It is known that whenever NWP model rainfall accumulation amounts are high, the values are unreliable, and so these parameters tend to be excluded from PoP models on statistical grounds. Therefore, it was decided to use rainfall indicator variables instead, i.e. rainfall variable = 0 for less than or equal to 0.01mm of rain, and rainfall variable = 1 for greater than 0.01mm of rain. These gave higher statistical contributions than the accumulations. The criterion of 0.01mm for model rainfall is different to that for observed rainfall. This model rainfall criterion was chosen using scatter plot analysis. It was decided that a more complicated statistical analysis was not necessary.

In the statistical investigation, a weighting is put on each parameter in the PoP model to show its importance. Different stations and different forecast times have different weightings on each parameter, giving a distribution of weights. Divergence and vorticity often have high weightings, usually at levels 4, and MSLP is always important. Dew point, particularly at lower levels, is often highly weighted and there is always a significant weight on the wind direction, particularly at a coastal station. Within this general pattern there can be some fluctuation, with some parameters being particularly favoured by some stations. There can also be fluctuations during different months of the year, and whenever there is a major NWP model change. This set of parameters, for each forecast time, time of day and station, is known as the NWP 'ascent' data.

2.3 Updateable Model

As the NWP model and the weather vary with time, it is necessary to have a system that copes with changes due to seasonality and to model updates. The MOS products adapt to changes by having an 'updateable' formulation. This process is described below, (see also Fig. 1).

At the end of each month (January 95, say), the observational and NWP parameter data, for that month, are extracted and arranged by validity time. The monthly averages and monthly variances (spread of values), for each observation and NWP parameter, are calculated using a simple time series regression model. The individual departures of each parameter from its monthly average are computed for all 31 days. These departures are squared and summed over the 31 days. The departures for each pair of parameters are also multiplied together and summed over the 31 days. The above results are stored in a matrix, which can be regarded as a concise summary of the month's data (actual January 95). This matrix is known as 'The Sum-

of-Squares-and-Products Matrix' (SSP). It is a cumulative form of the Covariance matrix and is used to derive the regression equations.

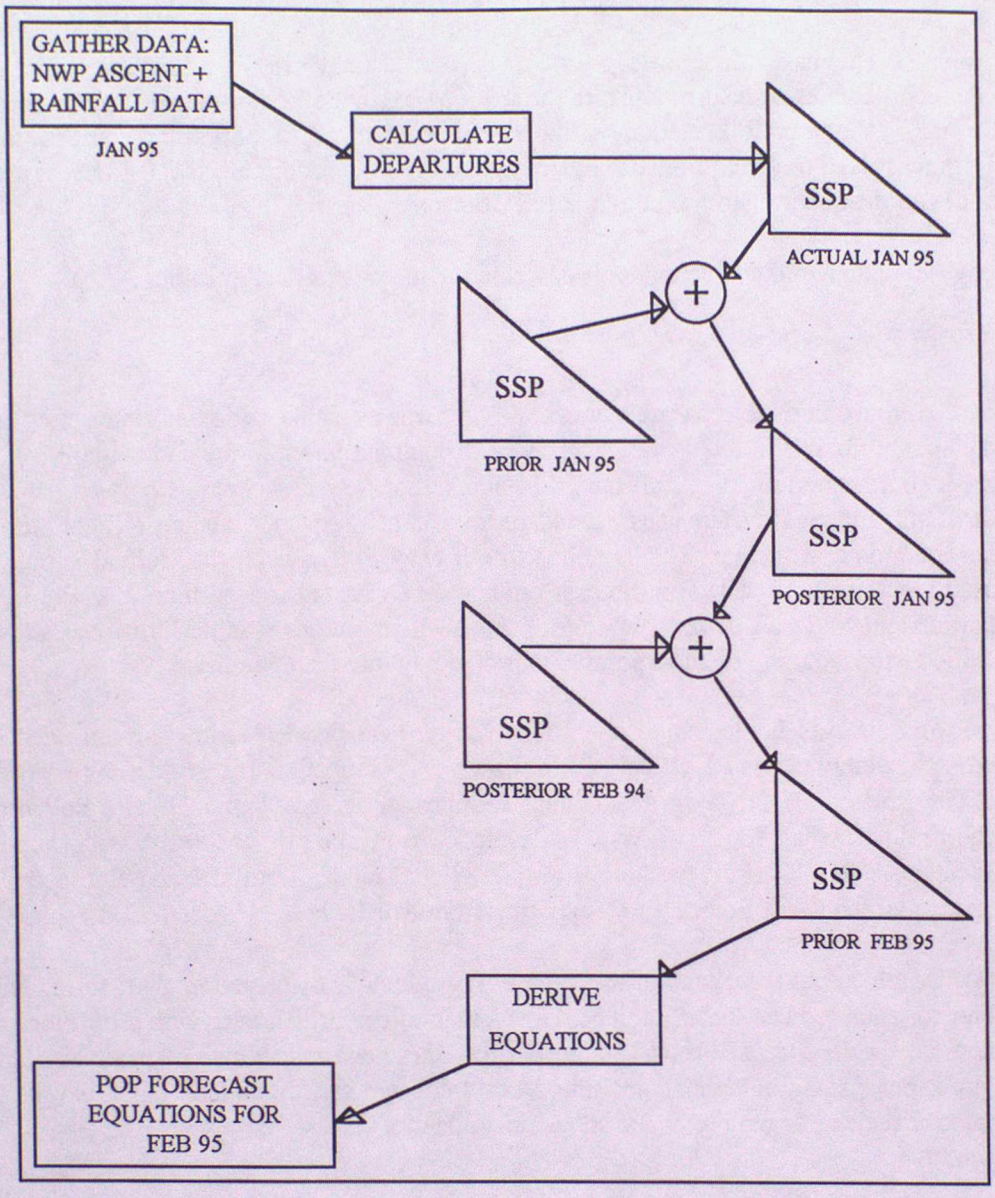

FIG. 1 : Schematic of MOS updating for PoP

Unfortunately, at this point there are only 31 days (at most) of data, which is very small for such a large statistical model as the PoP MOS. However, since the updateable model can be run over many years, previous data is available, i.e. the previous January and the previous month. Selected past data can be accumulated to give many more days to use in the statistical model. Therefore, to extract next month's (February 95) equations, the previous month's (January 95) accumulated SSP summary (known as the Prior), which was derived at the beginning of January 95, is used. This is added to the actual SSP summary for January 95, derived as above, to produce the final SSP summary (known as the Posterior) for January 95. Then, a weighted proportion of the SSP summary, of the same month last year (February 94), is added to a weighted proportion of the Posterior for January 1995. This weighting is important during model changes. By decreasing the weighting on old data, new data becomes relatively more important. With effectively a smaller number of days in the SSP summaries, it

is possible for the MOS products to adjust more quickly to the 'altered' NWP parameters. The new SSP summary gives an estimator (Prior) of next month's summary (February 95).

The Prior SSP summary for February 95 can be used with various statistical techniques to derive the coefficients for next month's (February 95) MOS PoP equations, to use in forecast mode. Finally to obtain PoP estimates, the coefficients for each particular combination of station, forecast lead time and time of day are applied to the appropriate NWP forecast ascent. The result can then be transformed into the PoP forecast.

The above statistical updateable model is described in more detail in Appendix A.

2.4 PoP Processing

PoP was developed in three separate stages. The first was as single grid point time series, going from 1984 to the end of 1989, where each grid point/station set was individually updated through the 6 year period. When all the grid point/station sets were complete up to the end of 1989, the full updating system was started on a monthly sequence, where all stations were updated one month at a time. This continued until May 1991, when the Unified Model took over from the 15 level model. The forecast times were expanded from a limit at T+48 to all 6 hour periods out to T+72. A re-weighting of the SSP summaries was performed to allow the new Unified Model data to be incorporated more quickly into the updating.

The PoP product was implemented operationally in November 1992, in chart format for the CFO. After a trial until May 1993, the CFO chose the specification of three new PoP products: Global UK PoP, LAM UK PoP and Global European PoP (see Table 1). The PoP product from the Limited Area Model (LAM) was developed from the original PoP product, updating from October 1991. The PoP products from the Global model, both UK and European, were developed from the LAM PoP product, updating from April 1993.

In the CFO, the output from each of the three PoP products is displayed in chart form. There is one chart for each forecast time. Each contains a map of the British Isles with a PoP forecast at each station, for the specified 6 or 12 hour period. These charts can also be made available on DOCFAX, but instead bulletins containing PoP tables will shortly be distributed via the ODS. Examples of the charts and tables are shown in Appendix C.

3. Verification

3.1 Verification Statistics

To assess the performance of the PoP models, a number of fairly standard verification and evaluation statistics have been used. Probability forecasts are less easy to assess than, for example, maximum temperature forecasts. The value and the quality of temperature forecasts are easily understood by the forecaster. A good forecast will be within a few degrees of the observation. A valuable forecast is one in which an extreme temperature, or a change from the previous day, is indicated and the change does happen. Such a forecast can be more than a few degrees out, and the forecaster will still accept it as valuable (although a simple statistical verification may not see it that way). However, probabilities are restricted between 0 and 1 and therefore it is difficult to appreciate the meaning of a probability outlier. Suppose the forecast probability of precipitation at a station was 95%, but it actually stayed dry. The forecast cannot statistically be judged as 'wrong', because according to the forecast, it would stay dry on 5 out of 100 occasions. It just might be one of those occasions when all the stations around this

station reported rain, but this one did not. Alternatively, the forecast may just have been completely wrong.

3.2 Brier Score

To measure the performance of temperature forecasts, Root Mean Square error, Mean error, Largest and Smallest error, Reduction in Variance, etc. are used, either as absolute values or relative to the natural fluctuations of the station values. There are some related statistics for probabilities. One such statistic is the 'Brier Score', which is a 'Mean Square Error' score. If 'f_i' denotes the forecast probability for the i^{th} occasion (ranging between 0 and 1) and 'o_i' is an indicator variable for the i^{th} observation (with $o_i = 1$ being an observed precipitation event and $o_i = 0$ being a 'dry' event), then the Brier Score (BS) can be represented by:

$$BS = \frac{\sum_{i=1}^{N} (f_i - o_i)^2}{N} \qquad \text{EQUATION (1)}$$

where N is the total number of events. This formula gives a value of zero for perfect forecasts, i.e. f_i always being 0 or 1 and always correct, and an increasing value for reducing accuracy. If a precipitation forecast were to be based on the toss of a coin, say heads it would rain, tails not, then the Brier Score would yield a value of 0.25. This would be the result of a random forecast. However, the Brier Score is of very limited value as an absolute statistic. The actual value a good forecasting model achieves is very dependent on the number of wet days in the period being verified. If the number of wet days is very small, the Brier Score for a good forecast can become very small. Therefore, a Brier Score must be assessed relative to other scores.

3.3 Skill Score

To compare one forecast model with another, a statistic known as the 'Skill Score' is used. The formula for the Skill Score (SS) is:

$$SS = 1 - \frac{BS_f}{BS_r} \qquad \text{EQUATION (2)}$$

where BS_f is the Brier Score of the forecast model, and BS_r is the Brier Score of the model to which the forecast model is being compared. Often this reference Brier Score is the Brier Score that would have occurred with a degree of hindsight, i.e. if the relative frequency of wet days over the comparison period were to be known in advance. This is known as the 'Sample Climatology'. If, for example, there were 3 wet days in a 30 day period, the forecast probability (for every day) would be 0.1 (=3/30), while the observed variable is 1 for the 3 wet days and 0 for the 27 dry days. Therefore using Equation (1), the Sample Climatology Brier Score would be:

$$BS_r = \underbrace{\sum_{i=1}^{3} \frac{(0.1-1)^2}{30}}_{\text{wet days}} + \underbrace{\sum_{i=1}^{27} \frac{(0.1-0)^2}{30}}_{\text{dry days}} = 0.09$$

The Skill Score, which can be stated as percentages, has a range of $-\infty$ to 1, with values 0 to 1 representing improvement on the reference model. The Skill Score is still not perfect, although much of the dependency on the number of wet or dry days (characteristic of the Brier Score) is removed in the Skill Score. However, if the number of wet (or dry) days is a small percentage

of all the days in the period, then the Sample Climatology Brier Score will be very small and hard to beat. In fact if every day was wet (or dry), the Sample Climatology Brier Score would be zero and the Skill Score would be-∞!

3.4 Reliability

Another statistical summary, which is actually a component of the Brier Score, is used in verifying the skill of probability forecasts. This is Reliability.

Reliability is the property that, if for example 10% is the forecast category, then over all occasions that 10% is forecast, there will be precipitation exactly 10% of the time. Reliability diagrams are formed by plotting the observed frequency against the forecast probability for individual forecast categories, e.g. 5% - 10%. The Reliability can be assessed numerically, or by looking at the deviation of the plot from the ideal, i.e. the 45° line. If the plotted curve lies below the 45° line, then the probability of precipitation is being over-forecast. If the curve lies above the 45° line then this indicates under-forecasting of this category. That is, if it rained on 38% of occasions when 30% was forecast, then the category was under-forecast. In principle, using these curves a forecast can be re-calibrated. If for example, a model is consistently under-forecasting by 10%, this can be taken into consideration either by putting a fix in the model, or by the forecaster adding 10% to each forecast.

4. Results

4.1 Skill Scores - Geographical Spread

Figure 2 shows the geographical pattern of average Skill Scores in 1994, at T+24 for the Global UK PoP product. From the graph, it can be seen that the Skill Scores for each geographical area, were all above 20%. This represents the percentage improvement that the PoP model had over Sample Climatology. Since Sample Climatology has an element of hindsight, this result was good. Eastern England and Eastern Scotland had lower Skill Scores compared to the other areas. This was because these areas were drier than the other areas. This affected the Skill Scores, as they are dependent on the number of wet (or dry) days, as explained in Section 3.3. At longer forecast lead times, the Skill Scores were smaller but had the same geographical pattern.

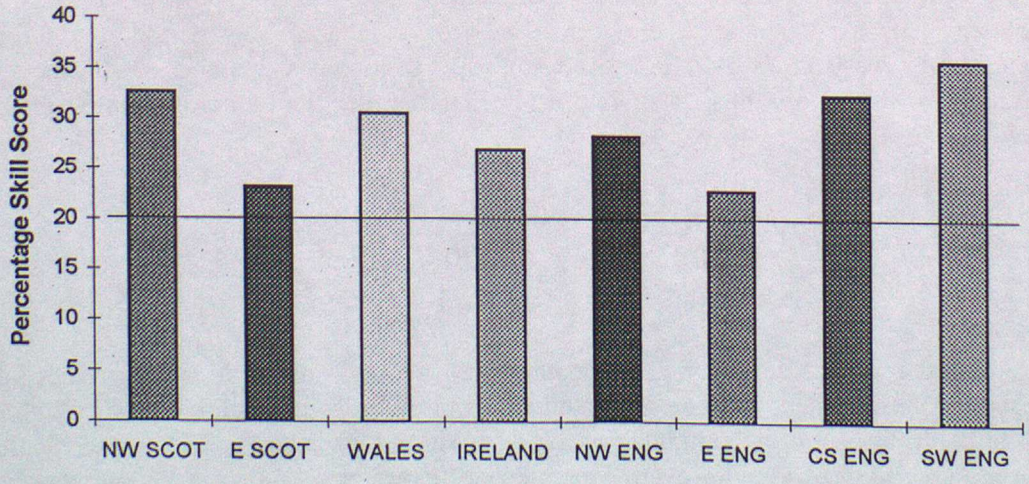

FIG. 2 : Geographical pattern of GLUK PoP average Skill Scores at T+24 for 1994

The geographical pattern of Skill Scores in 1994, at T+36 for the LAM UK PoP product, is shown in Fig. 3. Eastern England and Eastern Scotland had lower Skill Scores compared with the other areas, which was seen before in the Global UK PoP product. Apart from Eastern Scotland, the Skill Scores were all above 15%. This result was good, considering that T+36 is the longest forecast lead time in the LAM UK PoP model. Even the Skill Scores in Eastern Scotland should probably be considered good. The hindsight aspect of Sample Climatology was more significant when there were few actual rain days, and the PoP model had to work hard to obtain a positive Skill Score.

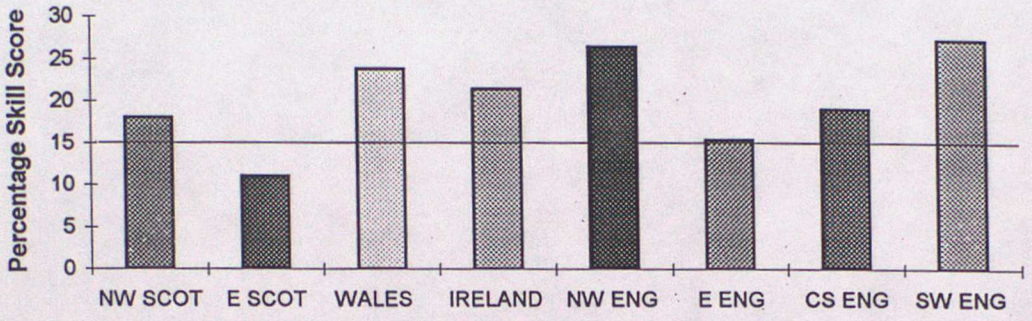

FIG. 3 : Geographical pattern of LAM UK PoP average Skill Scores at T+36 for 1994

Fig. 4 shows the geographical pattern of average Skill Scores in 1994, at T+72 for the Global European PoP product. The Skill Scores were all between 10 and 20%, which was good for T+72. Stations in the Russian area have had to be removed from the verification results and temporarily from the European PoP daily forecasts. It was belatedly recognised that Russian stations have different reporting practices than those expected by the current MOS processing.

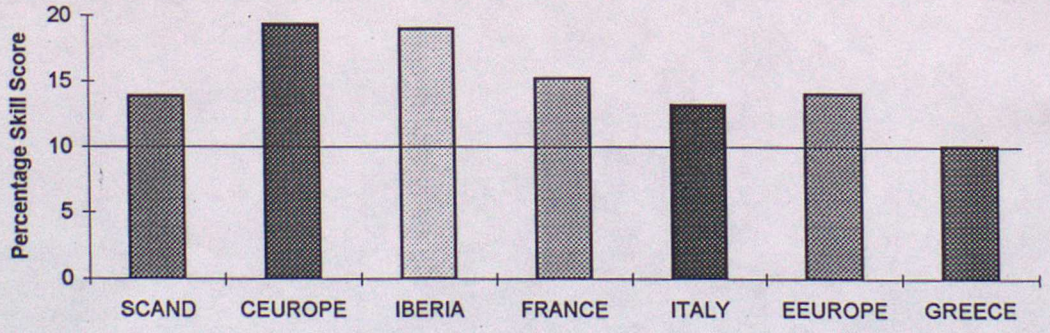

FIG. 4 : Geographical pattern of GLEU PoP average Skill Scores at T+72 for 1994

4.2 Skill Scores - Time dependency

Figs. 5, 6 and 7 show the seasonal variation of average Skill Scores with forecast lead time, for the three PoP products. There are three major effects to consider, when examining these graphs.

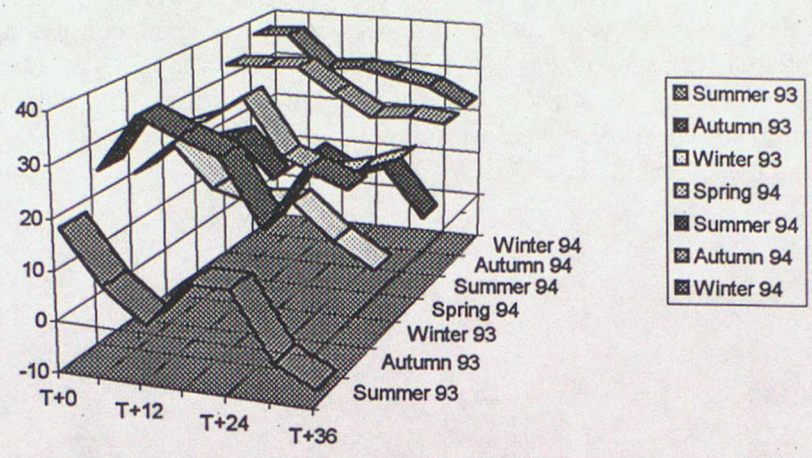

FIG. 5 : Seasonal variation of LAM UK PoP average Skill Scores with forecast lead time

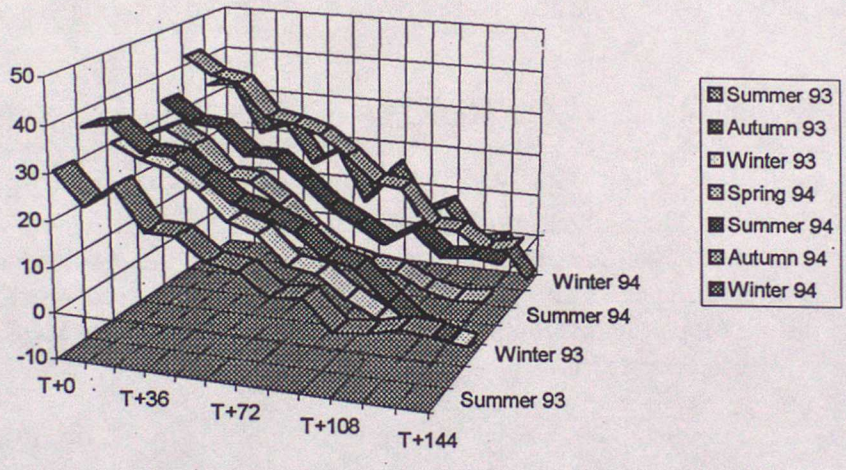

FIG. 6 : Seasonal variation of GLUK PoP average Skill Scores with forecast lead time

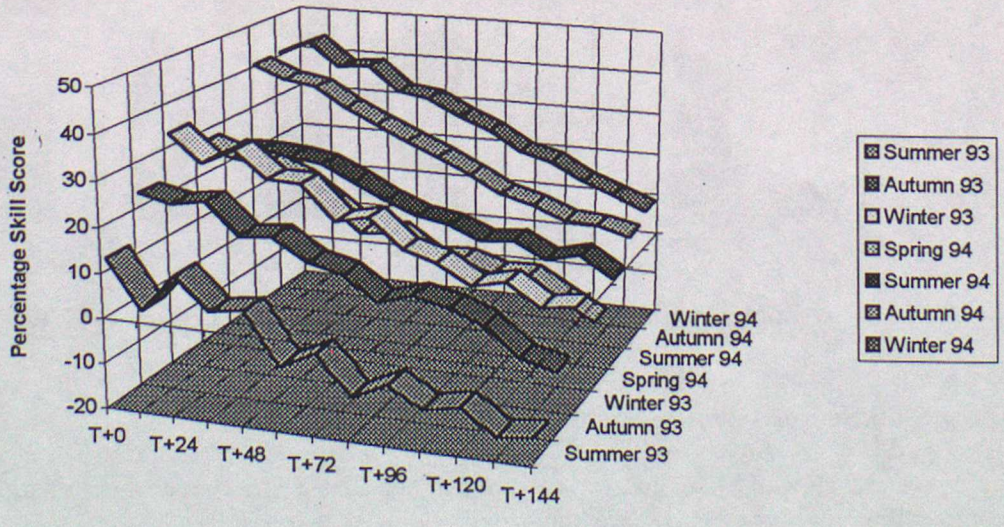

FIG. 7 : Seasonal variation of GLEU PoP average Skill Scores with forecast lead time

In general, as the forecast lead time increases, the Skill Scores decrease. For the Global PoP products, the Skill Scores are mainly more than 15% out to T+72. This result is good, considering that the PoP model was originally developed to only forecast out as far as T+72. The Skill Scores, for the LAM PoP product, are mainly above 20% for all forecast lead times, which is thought to be a very good result. The best Skill Scores are around 40% and occur in Winter at early forecast lead times.

The Skill Scores for Summer 1993 for all the PoP models are not as good as in later seasons, as Summer 1993 was the season in which the updating was started. At this time, there was least accumulated knowledge in the Updateable MOS system. The Skill Scores generally improve from 1993 to 1994.

It can be seen from all three graphs that the Skill Scores are inclined to be higher in the Autumn and Winter seasons, rather than the Spring and Summer ones. This is because Spring and Summer are drier than Autumn and Winter. In the Summer for example, a station can be dry for long periods of time. Therefore, this affects the Skill Scores, as they are dependent on the number of wet or (dry) days, as explained in Section 3.3.

4.3 Reliability Diagrams

Reliability diagrams were plotted for the three PoP products (see Figs. 8, 9 and 10). On each graph, the x-axis is the PoP forecast probability in 5% categories, while the y-axis is the observed rainfall frequency in each category. The ideal follows the 45° line.

Fig. 8 shows the Reliability diagram in 1994 at T+24 for separate geographical areas, for the Global UK PoP product.

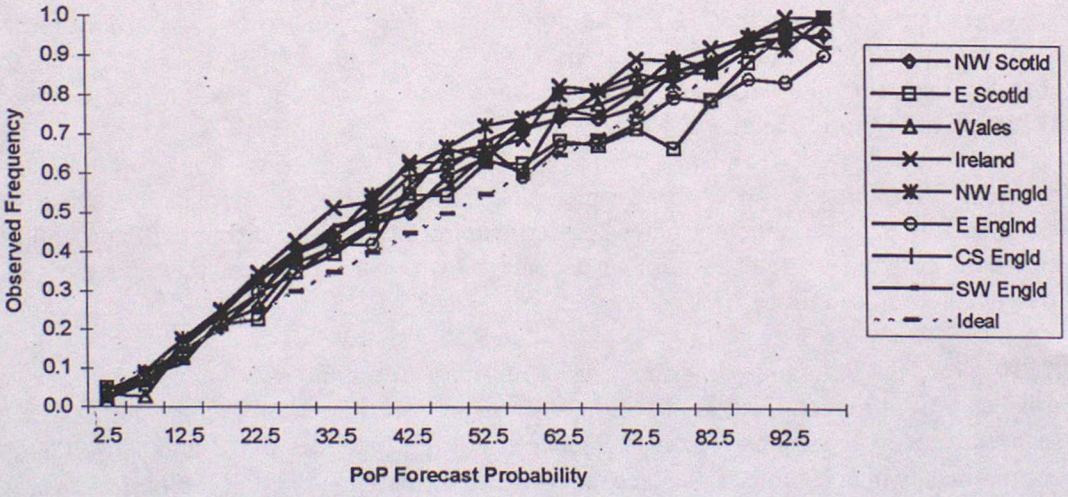

FIG. 8 : Geographical pattern of GLUK PoP Reliability at T+24 for 1994

From the graph, it can be seen that all the Reliability lines were close to the ideal line. However there was a persistent amount of under-forecasting between PoP probabilities of between 20 and 85%. In the 75-80% category, precipitation in Eastern Scotland has been over-forecast, while in the other areas it has been either correctly forecast or under-forecast. At the higher PoP probabilities, there was larger variation in Eastern Scotland Reliability than in the other areas, due to the smaller number of forecasts of high probabilities. A Reliability diagram

should be accompanied by a histogram of the frequency of each forecast probability, but this would be confusing with different areas.

The Reliability diagram in 1994 at T+24 for separate areas, for the LAM UK PoP product is shown in Fig. 9.

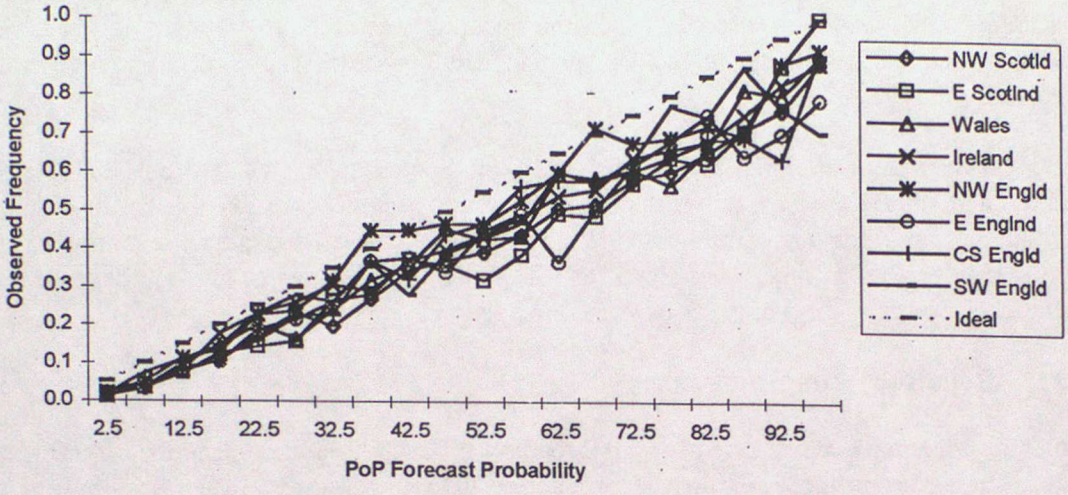

FIG. 9 : Geographical pattern of LAM UK PoP Reliability at T+24 for 1994

The Reliability lines were all close to the ideal line up to the 50% category. However, over-forecasting occurred for almost all areas above this category. Also the areas became more variable as the PoP probability increased. Figs. 8 and 9 are both for T+24. From these Reliability diagrams, the LAM UK PoP model appeared to be not as good as the Global UK PoP model, at PoP probabilities above 50%.

The under-forecasting and over-forecasting, in Figs. 8 and 9 could be explained by a slight departure from the assumptions made when deriving the algorithm to compute the probabilities. This could be fixed by re-calibration, but could be wrong for different times of the year or different forecast lead times.

Fig. 10 shows the Reliability diagram in 1994 at T+120 for all areas combined, for the Global European PoP product. As can be seen, like the LAM PoP model, this model was also consistently over-forecasting. However, between PoP probabilities of 10 and 50%, there is a constant bias, which could be taken account of when interpreting the PoP forecast. Above 50%, the Reliability drops away from the ideal line. Unlike earlier forecast lead times, this problem is not likely to be due to problems with the algorithm. At T+120, the model is not good enough to forecast rain with 95% certainty in a 12 hour period. In principle, a restricted range of probabilities ought to be used at forecast lead times higher than T+72. Since this has not been done, the PoP forecast is constrained to the full probability range, and therefore the above type of Reliabilities result.

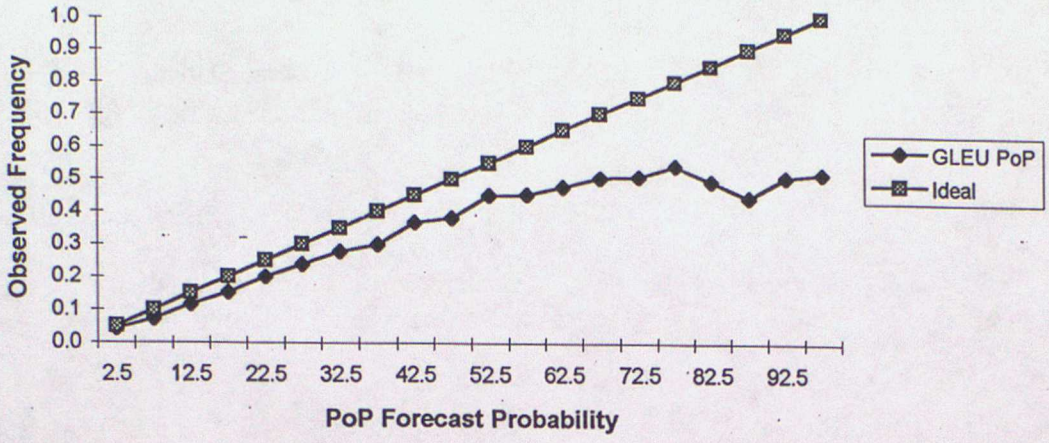

FIG. 10 : GLEU PoP Reliability at T+120 for 1994

5. Conclusion

The Global UK PoP and LAM UK PoP products have been operational in the CFO since Summer 1994, while the Global European PoP product was implemented in December 1994. As from May 1995, all three PoP products will be disseminated to the outstations via ODS.

The rationale for having any MOS product is to give an initial estimate to the forecaster, or a reasonable, low cost estimate to a user if there is no forecaster in the cycle. It should be remembered that the PoP models were derived from past data. The forecasts produced are based on what has happened in the past.

The Global UK PoP product shows good Skill at least out to T+72, but is slightly under-forecasting. However, the LAM UK PoP product shows good Skill at all its forecast lead times (out to T+36), but is slightly over-forecasting. The verification results (in Section 4), for the UK PoP models, show poorer results in Eastern areas. These 'poor' results are, at least in part, due to the bias of the statistical scores in drier areas, which makes it difficult to obtain a 'good' score. When the two UK PoP models were compared at their common forecast times, it would appear that the Global UK PoP model is often better than the LAM UK PoP model. This is likely to be explained by, for example, the time period for the LAM PoP product being 6 hours, while that for the Global PoP product is 12 hours. It may be easier to forecast scattered rain in a 12 hour period, than in a 6 hour period. The Global European PoP product shows good Skill at least out to T+72 but is slightly over-forecasting.

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Appendix A - Statistical Model in the MOS Updating

Fig. 1 showed an outline of the Updateable MOS system. In this system, one month of daily events are collected for every station and every relevant combination of forecast run and forecast lead time. They are gathered by verification or validity time, and each 'event' is represented by a combination of NWP model ascent data and observed synoptic data which are all valid at approximately the same time (some observed data are measured over a period, while most NWP data are valid at a spot time within the period). The scheme in Fig. 1 represents the processing for one such set of this data.

If the set of variables from the NWP model, $\{M_i\}$, i = 1...r, and the set of observed station data, $\{O_j\}$, j = 1...s, are gathered into a combined vector X of size (r+s), one event or case is represented by this data. All the values within each vector X are valid at the same time, but also all the NWP data in each X come from the same forecast run. That is, this implementation of MOS allows only one forecast time from one forecast run in each case, with no interpolation between forecast times. For observed data, if any parameter is really a binomial (2 variables) or multinomial (3 or more variables) event, the set s, could be expanded to include one member of O, for each distinct class of binomial or multinomial data.

Actually in practice in the current MOS PoP, the means and variances of the binomial data are not computed. It is the raw data that is used. This is because in an earlier model, some stations produced biased results.

1. Converting to Standardised Anomalies

After gathering the month of data, the sets of the (r+s) variables in X are converted to standardised anomalies (except for the binomial variables), by treating each variable separately as a month of scalars.

$$Z = \{z_i\} \; ; \; z_i = (x_i - \mu_{m,i}) / \sigma_{m,i} \quad ; \quad i = 1...(r+s) \qquad (A.1)$$

where m is the month number (1...12), and $\mu_{m,i}$ and $\sigma_{m,i}$, the monthly mean and standard deviation, are computed through a recursive time series model. Recursive Least Squares time series models are very similar in arithmetic form to Kalman Filters (references in Young 1984). The form of the model (dropping index i) is now:

$$\overline{\mu}_m = \hat{\mu}_m + \varepsilon_m = \alpha_1 + \alpha_2 . \mu_{m-1} + \alpha_3 . \cos\theta + \alpha_4 . \sin\theta + \varepsilon_m \qquad (A.2)$$

$$\hat{\sigma}_m^2 = (a_1 \; n_{m-1} \; \hat{\sigma}_{m-1}^2 \; + \; a_2 \; n_{m-12} \; \hat{\sigma}_{m-12}^2 \; + \overline{\sigma}_m^2 \; + \; \varepsilon_m^2 \;) \; / \; n_m \qquad (A.3)$$

$$n_m = a_1 \; n_{m-1} + a_2 \; n_{m-12} + 1 \qquad (A.4)$$

where: m denotes the latest month; m-1 last month, and m-12 this month last year,
$\overline{\mu}_m$ and $\overline{\sigma}_m^2$ are the sample means and variances of the month just finished,
θ is the phase of the month within the annual cycle,
ε_m is the difference between the updated estimate of the monthly mean $\hat{\mu}_m$ and the sample value $\overline{\mu}_m$,
$\hat{\sigma}_m^2$ is the model estimate of the parameter variance for this month,
n_m is the weighting or the effective number of months in the computation of σ^2.

The coefficients α_1, α_2, α_3 and α_4 are computed through recursive regression and are therefore dependent on the monthly mean data. However, the weights on the annual cycle can be forced to be zero for terms that do not have an annual cycle in the mean. The coefficients a_1 and a_2, on the other hand, have been chosen arbitrarily, and the values picked such that the estimates give a stable and well-behaved model of the variance. In a trial to make the variance weighting also recursive, the results were found to be particularly unstable. This could have been investigated further, but since the fixed weighting seems to work well, this form was chosen.

The model for the monthly mean value (A.2) has an annual cycle model through an explicit sinusoid (α_3 and α_4), a term for the overall mean (α_1), as well as an autoregressive component with a lag of one step, i.e. one month (α_2). This seems to work well for UK and most European stations. For other places with different climates, where the annual cycle is large but with marked variations from one year to another, there is evidence that this model does not fit as well. The model (A.3) for $\hat{\sigma}_m^2$ has autoregressive components at lag 1 and lag 12, because where there is an annual cycle present, individual months can be particularly variable, and the signal to noise ratio is much lower than for the annual cycle in the mean value. Before this model was chosen, previous versions also had a full autoregression for the mean values. It was found that the sine component of the annual cycle was not adequately modelled, and for estimating the mean in forecast mode, was subject to lag errors perhaps due to insufficiently stable estimates.

In the present model, the coefficients α_3 and α_4 have the values of the full annual cycle coefficients in the expected values (say A and B) only if α_2 is zero; otherwise they take reduced values due to the phase shift introduced by the one month autoregression. Since the annual cycle is generally much larger than the day to day variation, or more particularly the month to month variation, once the estimates have locked on to a full year of data, the estimates do not seem to show lag errors in forecast mode.

2. Updating of Correlation Structures

The standardised anomalies are created for all continuous, non-binary variables in the vector X. Where a term of the set of the combined NWP and observation vector is binary, let $\mu = 0$, and $\sigma = 1$. The set of N anomalies, for month m in (A.1), are converted to Sums-of-Squares-and-Products (SSP) form. This is just an unnormalised form of the covariance or correlation matrix. The GENSTAT SSP structure also stores the means and number of degrees of freedom of the sample, as ancillary structures. Although the mean values of the standardised anomalies are zero over a long period, they need not be zero in a sample, or where the variable is a binary or interaction term (if they are being used).

The set of NWP variables in X must have previously been chosen, as they are known or suspected to vary with the observed data such that there is predictive power. Reducing the array size at this stage limits the types of regression model or discriminant function that can be formed later, but also reduces the storage and computational burden. When creating a new MOS product, a survey of the range of likely models, and the variation with season, station, forecast time, and time of day, should be quite thorough.

The Sample SSP for month m is:

$$\mathrm{SSSP(m)} = \sum_{i=1}^{N} (z_{ij}\, z_{ik}) \qquad (j, k+1 \ldots r+s) \qquad (A.5)$$

where i is now the index for the day of the month, and j and k are indices of the components of each standardised anomaly vector. The final SSP structure for month m is called the Posterior SSP matrix, SSPPO(m). It is calculated from the Prior SSP structure, SSPPR(m), and the sample SSSP(m). The prior SSP is found from the posterior matrices for month (m-1) and (m-12), which would have been calculated at the beginning of month m, before the sample month of data had been gathered. It is computed from month (m-1) to include the effects of recent data, and from month (m-12) to allow an annual cycle in the correlations, to emphasise the behaviour at this time of year. The weightings of the two past models are arbitrary, but can be varied to incorporate the effects of recent numerical model changes.

$$SSPPR(m) = a.\ SSPPO(m-1) + b.\ SSPPO(m-12) \qquad (A.6)$$

$$SSPPO(m) = SSPPR(m) + SSSP(m) \qquad (A.7)$$

Typical weights of 0.59 for a, and 0.39 for b, give exponential weights of $(0.59)^2$ for 2 months ago, $(0.59)^3$ for 3 months ago, and $(0.39)^2$ for this month two years ago, etc., giving an eventual equilibrium number of degrees of freedom of around 1500.

3. Regression Models and Discriminant Functions

The SSP structure, being an unnormalised covariance matrix, is readily transformed to least squares regression coefficients via the Normal Equations. Discriminant Analysis is usually specified using two covariance matrices, the Between-Groups-SSP and the Within-Groups-SSP. Discriminant Analysis is a technique to find a linear function (or set of functions) which best differentiates between the different group (or groups). These 'classification functions' are used to assign probabilities that an individual case belongs to the different groups. The classification function is a linear function of the input (NWP) variables, and measures the 'distance' from the centroid of each group. They are optimised to the data, and the form of the optimisation finds a projection in the co-ordinate system, of all the NWP variables, that maximises the Between-Groups to the Within-group variance ratio, in an analogous manner to finding the largest Variance Ratio statistic.

The single SSP structure of the Updateable MOS can be manipulated to yield the two matrices, but it involves inverting one large matrix for each different observed variable. A mathematically identical solution is to use Canonical Variate Analysis to find the Classification functions. This has the advantage of inverting only one large matrix for all the observed variables. Canonical Variate Analysis finds the linear functions defined on the NWP variables and linear functions of the observed variables, that have the highest possible correlation with each other. Since in this case, the observed variables are discrete binary sets, the linear forms can be converted to give the desired classification functions.

4. Forecast Equations

To use the regression equations in forecast mode an equation that will be valid for next month must be found. The model for the annual cycle (A.2, A.3 and A.4) can be used to estimate the mean and variance for every parameter for next month, μ_{m+1} and σ_{m+1}^2. Then, the prior SSP structure SSPPR(m+1) can be found from (A.6), and this can be used to find regression equations and classification functions. The regression equation coefficients can be re-scaled directly using μ and σ, or the process of standardising each forecast ascent can be applied formally. In this formal process, the regression weights are applied to give a forecast, standardised observed variable estimate, and this term is unstandardised using the forecast of its mean and standard deviation, to give the proper scaled forecast of the observed parameter.

Appendix B - Lists of PoP Stations

The following table contains the stations used in the Global UK and the LAM UK PoP products:

WMO NUMBER	STATION NAME	LAT/LON
03002	BALTASOUND SAWS	6046N 0052W
03005	LERWICK (S. SCREEN)	6008N 0111W
03006	SELLA NESS SAMOS	6027N 0116W
03008	FAIR ISLE	5932N 0138W
03017	KIRKWALL	5857N 0254W
03022	BENBECULA	5728N 0722W
03026	STORNOWAY (AIRPORT)	5813N 0619W
03031	LOCH GLASCARNOCH	5743N 0453W
03034	AULTBEA SAWS	5752N 0538W
03044	ALTNAHARRA	5817N 0426W
03047	TULLOCH BRIDGE SAWS	5652N 0443W
03049	CAPE WRATH	5837N 0500W
03062	TAIN RANGE SAWS	5749N 0358W
03063	AVIEMORE	5712N 0350W
03066	KINLOSS	5739N 0334W
03068	LOSSIEMOUTH	5743N 0319W
03075	WICK	5827N 0305W
03080	ABOYNE SAWS	5705N 0250W
03088	INVERBERVIE SAWS	5651N 0216W
03091	DYCE	5712N 0212W
03100	TIREE	5630N 0653W
03102	ORSAY	5540N 0630W
03111	MACHRIHANISH	5526N 0542W
03132	WEST FREUGH (SAWS)	5451N 0457W
03140	ABBOTSINCH	5552N 0426W
03144	STRATHALLAN AIRFIELD SAWS	5619N 0344W
03153	DUNDRENNON (SAWS)	5448N 0400W
03155	DRUMALBIN	5537N 0344W
03158	CHARTERHALL SAWS	5542N 0223W
03160	TURNHOUSE	5557N 0321W
03162	ESKDALEMUIR (S. SCREEN)	5519N 0312W
03171	LEUCHARS	5623N 0252W
03204	RONALDSWAY	5405N 0438W
03210	ST BEES HEAD (SAWS)	5431N 0336W
03212	KESWICK (SAWS)	5437N 0310W
03214	WALNEY ISLAND (SAWS)	5407N 0315W
03215	ASPATRIA	5446N 0319W
03220	CARLISLE SAWS	5456N 0258W
03224	SPADEADAM	5503N 0233W
03225	SHAP SAWS	5430N 0242W
03226	WARCOP RANGE (SAWS)	5434N 0225W
03240	BOULMER	5525N 0136W
03246	NEWCASTLE WC SAMOS	5459N 0136W
03257	LEEMING	5418N 0132W
03261	DISHFORTH	5408N 0125W
03262	TYNEMOUTH	5501N 0125W
03266	LINTON ON OUSE	5403N 0115W
03302	VALLEY	5315N 0432W
03305	CAPEL CURIG	5306N 0356W

03313	RHYL SAWS	5315N 0330W
03316	CROSBY	5330N 0304W
03321	HAWARDEN SAWS	5310N 0259W
03322	AUGHTON	5333N 0255W
03334	RINGWAY	5321N 0216W
03344	BINGLEY	5349N 0152W
03347	LEEDS WEATHER CENTRE	5348N 0134W
03354	WATNALL	5300N 0115W
03360	FINNINGLEY	5329N 0100W
03373	SCAMPTON	5319N 0033W
03377	WADDINGTON	5310N 0031W
03379	CRANWELL	5302N 0030W
03384	LECONFIELD SAWS	5352N 0026W
03391	CONINGSBY	5305N 0010W
03405	ABERDARON	5347N 0444W
03414	SHAWBURY	5248N 0240W
03453	COTTESMORE	5243N 0040W
03462	WITTERING	5237N 0028W
03469	HOLBEACH SAWS	5252N 0009E
03482	MARHAM	5239N 0034E
03488	WEYBOURNE SAWS	5257N 0108E
03492	NORWICH WEATHER CENTRE	5238N 0119E
03495	COLTISHALL	5246N 0121E
03496	HEMSBY	5241N 0141E
03502	ABERPORTH	5208N 0434W
03503	TRAWSCOED (SAWS)	5220N 0357W
03521	MADLEY	202N 0251W
03527	GREAT MALVERN	5207N 0218W
03529	PERSHORE SAWS	5209N 0202W
03534	ELMDON	5227N 0145W
03544	CHURCH LAWFORD (SAWS)	5222N 0120W
03560	BEDFORD SAWS	5213N 0029W
03566	WYTON	5221N 0007W
03590	WATTISHAM	5207N 0058E
03604	MILFORD HAVEN C.B	5142N 0503W
03605	PEMBREY SANDS	5143N 0422W
03609	MUMBLES HEAD	5134N 0359W
03647	LITTLE RISSINGTON SAWS	5152N 0141W
03649	BRIZE NORTON	5145N 0135W
03658	BENSON	5137N 0106W
03672	NORTHOLT	5133N 0025W
03683	STANSTED	5153N 0013E
03693	SHOEBURYNESS	5133N 0050E
03707	CHIVENOR	5105N 0409W
03712	TIVINGTON	5112N 0332W
03715	RHOOSE	5124N 0320W
03717	CARDIFF WEATHER CENTRE	5129N 0310W
03726	BRISTOL WEATHER CENTRE	5127N 0236W
03740	LYNEHAM	5130N 0159W
03745	NETHERAVON	5115N 0146W
03746	BOSCOMBE DOWN	5110N 0145W
03749	MIDDLE WALLOP	5109N 0134W
03761	ODIHAM	5114N 0057W
03763	BRACKNELL BEAUFORT PK	5123N 0047W
03768	SOUTH FARNBOROUGH SAWS	5117N 0046W
03772	HEATHROW	5129N 0027W
03776	GATWICK	5109N 0011W
03779	LONDON WEATHER CENTRE	5130N 0007W

03781	KENLEY AIRFIELD SAWS	5118N 0005W
03790	EAST MALLING	5117N 0027E
03797	MANSTON	5121N 0121E
03803	SCILLY/ST MARYS (SAWS)	4955N 0618W
03808	CAMBORNE	5013N 0519W
03809	CULDROSE	5005N 0515W
03817	ST.MAWGAN	5026N 0500W
03823	CARDINHAM (BODMIN) SAWS	5030N 0440W
03827	MOUNT BATTEN	5021N 0407W
03840	DUNKESWELL	5052N 0314W
03853	YEOVILTON	5100N 0238W
03862	HURN	5047N 0150W
03865	SOUTHAMPTON WEATHER CENTRE	5054N 0124W
03882	HERSTMONCEUX W/E	5054N 0020E
03894	GUERNSEY (AIRPORT)	4926N 0236W
03903	ST ANGELO	5424N 0739W
03916	BALLYPATRICK FOREST	5511N 0610W
03917	BELFAST/ALDERGROVE (AIRPORT)	5439N 0613W
03920	LONG KESH	5429N 0606W
03923	GLENANNE	5414N 0630W
03953	VALENTIA OBSERVATORY	5156N 1015W
03955	CORK AIRPORT	5151N 0829W
03957	ROSSLARE	5215N 0620W
03960	KILKENNY	5240N 0716W
03962	SHANNON AIRPORT	5242N 0855W
03965	BIRR	5305N 0753W
03967	CASEMENT AERODROME	5318N 0626W
03969	DUBLIN AIRPORT	5326N 0615W
03970	CLAREMORRIS	5343N 0859W
03971	MULLINGAR	5332N 0722W
03974	CLONES	5411N 0714W
03976	BELMULLET	5414N 1000W
03980	MALIN HEAD	5522N 0720W

The following table contains a list of the stations used in the Global European PoP product:

WMO NUMBER	STATION NAME	LAT/LON
01001	JAN MAYEN	7051N 0840W
01025	TROMSO/LAGNES	6819N 1855E
01028	BJORNOYA	7411N 1901E
01055	FRUHOLMEN LT HO	7106N 2400E
01078	SLETNES LT HO	7105N 2814E
01098	VARDO	7022N 3106E
01152	BODO	6715N 1424E
01271	TRONDHEIM/VAERNES	6328N 1056E
01317	BERGEN/FLORIDA	6023N 0520E
01415	STAVANGER/SOLA	5853N 0538E
01488	OSLO/FORNEBU	5953N 1037E
02186	LULEA/KALLAX	6533N 2208E
02464	STOCKHOLM/BROMMA	5921N 1757E
02512	GOTEBORG/SAVE	5747N 1153E
02636	MALMO/STURUP	5533N 1322E
02836	SODANKYLA	6722N 2639E
02929	JOENSUU	6240N 2938E

02935	JYVASKYLA/LUONETJARVI	6224N 2540E
02944	TAMPERE/PIRKKALA	6125N 2335E
02974	HELSINKI/VANTAA	6019N 2458E
03005	LERWICK (S. SCREEN)	6008N 0111W
03091	DYCE	5712N 0213W
03140	ABBOTSINCH	5552N 0426W
03334	RINGWAY	5322N 0216W
03726	BRISTOL WEATHER CENTRE	5127N 0236W
03772	HEATHROW	5129N 0027W
03827	MOUNT BATTEN	5021N 0407W
03917	ALDERGROVE	5439N 0611W
03955	CORK	5151N 0829W
03969	DUBLIN	5326N 0615W
06081	BLAVAND	5534N 0805E
06180	KOBENHAVN/KASTRUP	5538N 1240E
06240	AMSTERDAM/SCHIPOL	5218N 0446E
06408	OOSTENDE(PIER)	5114N 0255E
06451	BRUXELLES AIRPORT	5054N 0432E
06590	LUXEMBOURG	4937N 0613E
06660	ZURICH	4723N 0834E
06700	GENEVE/COINTRIN	4615N 0608E
06734	INTERLAKEN	4640N 0752E
07010	DUNKERQUE	5103N 0220E
07028	LA HEVE(LE HAVRE)	4931N 0004E
07110	BREST/GUIPAVAS	4827N 0425W
07157	PARIS/CH DE GAULLE	4901N 0232E
07190	STRASBOURG	4833N 0738E
07222	NANTES	4710N 0136W
07249	ORLEANS/BRICY	4759N 0145E
07280	DIJON	4716N 0505E
07299	BASEL-MULHOUSE	4736N 0731E
07434	LIMOGES/BELLEGARD	4552N 0111E
07460	CLERMONT-FERRAND	4547N 0310E
07481	LYONS/SATOLAS	4544N 0505E
07510	BORDEAUX/MERIGNAC	4450N 0042W
07630	TOULOUSE/BLAGNAC	4338N 0122E
07650	MARSEILLE/MARIGNANE	4327N 0513E
07690	NICE	4339N 0712E
07747	PERPIGNAN	4244N 0252E
07761	AJACCIO	4155N 0848E
08001	LA CORUNA	4322N 0825W
08027	SAN SEBASTIAN/IGUELDO	4318N 0203W
08141	VALLADOLID	4139N 0446W
08160	ZARAGOZA	4139N 0100W
08181	BARCELONA/PRAT	4147N 0204E
08221	MADRID/BARAJAS	4027N 0335W
08284	VALENCIA/MANISES	3930N 0028W
08306	PALMA DE MAJORCA	3933N 0244E
08314	MAHON/MENORCA	3952N 0414E
08348	CUIDAD REAL	3859N 0355W
08360	ALICANTE/EL ALTET	3817N 0033W
08373	IBIZA/ES CODOLA	3852N 0123E
08391	SEVILLE/SAN PABLO	3725N 0554W
08482	MALAGA/EL ROMPEDIZO	3640N 0429W
08487	ALMERIA	3651N 0223W
08495	GIBRALTAR	3609N 0521W
08509	LAJES	3845N 2705W
08515	SANTA MARIA	3658N 2510W

08521	FUNCHAL/S CATARINA	3241N 1646W
08545	PORTO/PEDRAS RUBRAS	4114N 0841W
08554	FARO	3701N 0758W
08579	LISBOA/GAGO CONTINHO	3846N 0908W
10147	HAMBURG/FUHLSBUTTEL	5338N 0959E
10224	BREMEN	5303N 0848E
10320	GUTERSLOH	5156N 0819E
10338	HANNOVER	5228N 0942E
10384	BERLIN/TEMPELHOF	5228N 1324E
10400	DUESSELDORF	5118N 0646E
10401	BRUGGEN	5112N 0608E
10405	LAARBRUCH	5136N 0608E
10410	ESSEN	5124N 0658E
10469	LEIPZIG/SCHKEUDITZ	5125N 1214E
10513	KOLN/BONN	5052N 0708E
10637	FRANKFURT/MAIN	5003N 0835E
10739	STUTTGART/CANNSTADT	4850N 0912E
10865	MUNCHEN/STADT	4808N 1133E
11036	WIEN/SCHWECHAT	4807N 1634E
11120	INNSBRUCK	4716N 1121E
11518	PRAHA/RUZYNE	5006N 1415E
12160	ELBLAG	5410N 1926E
12205	SZCZECIN(STETTIN)	5324N 1437E
12330	POZNAN	5225N 1650E
12375	WARSAWA-OKECIE	5210N 2258E
12424	WROCLAW-STRACHOWICE	5106N 1659E
12560	KATOWICE	5014N 1902E
12843	BUDAPEST/LORINC	4726N 1911E
12882	DEBRECIN	4729N 2138E
12982	SZEGED	4615N 2006E
13014	LJUBLJANA/BRNIK	4613N 1429E
13130	ZAGREB/MAKSIMIR	4549N 1602E
13209	PULA	4454N 1355E
13224	ZADAR/ZEMUNIK	4405N 1521E
13272	BEOGRAD/SURCIN	4449N 2017E
13455	HERCEG NOVI-IGALO	4227N 1833E
13586	SKOPJE-PETROVAC	4157N 2138E
15120	CLUJ	4647N 2334E
15614	SOFIA	4249N 2323E
16072	MONTE BISBINO	4552N 0904E
16080	MILANO/LINATE	4526N 0917E
16105	VENEZIA/TESSARA	4530N 1220E
16120	GENOVA/SESTRI	4425N 0851E
16149	RIMINI	4402N 1237E
16230	PESCARA	4226N 1412E
16242	ROMA/FIUMICINO	4148N 1214E
16289	NAPOLI/CAPODICHINO	4051N 1418E
16320	BRINDISI	4039N 1757E
16405	PALERMO/PUNTA RAISI	3811N 1606E
16460	CATANIA/FONTANAROSSA	3728N 1503E
16560	CAGLIARI/ELMAS	3915N 0903E
16597	LUQA	3551N 1429E
16622	THESSALONIKA/MIKRA	4031N 2258E
16641	KERKYRA (CORFU)	3937N 1955E
16716	ATHENS/HELLINIKON	3754N 2344E
16746	SOUDA (CRETE)	3533N 2407E
16749	RHODES/MARITSA	3623N 2614E
16754	IRAKLION (CRETE)	3520N 2511E

17601	AKROTIRI	3435N 3259E
22113	MURMANSK	6858N 3303E
22217	KANDALAKSA	6708N 3226E
22271	SOJNA	6753N 4408E
22522	KEM'PORT	6459N 3447E
22550	ARHANGEL'SK	6435N 4007E
22802	SORTOVALA	6143N 3043E
22820	PETROZAVODSK	6149N 3416E
22845	KARGOPOL'	6130N 3856E
26038	TALLIN	5925N 3248E
26063	LENINGRAD	5958N 3018E
26422	RIGA	5658N 2404E
26702	KALININGRAD	5442N02037E
26730	VILNIUS	5438N02500E
33008	BREST LITOVSK	5207N 2341E
33393	LVOV	4949N 2357E
40100	BEIRUT	3349N 3529E

Appendix C - Sample Tables and Charts

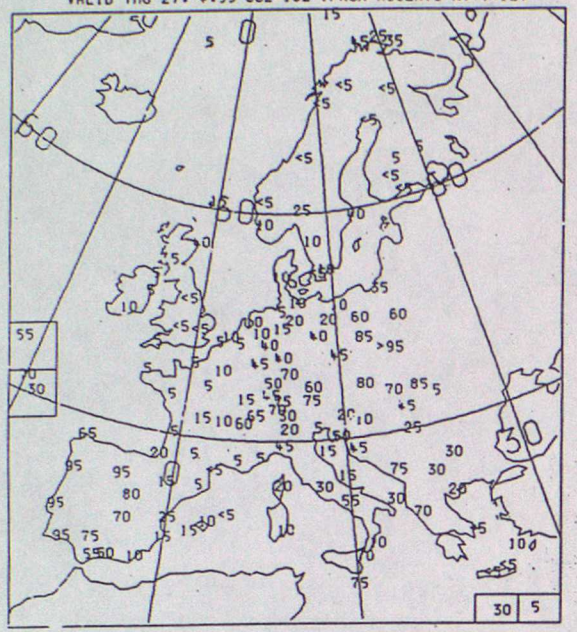
FXUK40
270000

LAM UK PROBABILITY OF PRECIPITATION FORECASTS 1
(FOR PREVIOUS 6 HOURS)

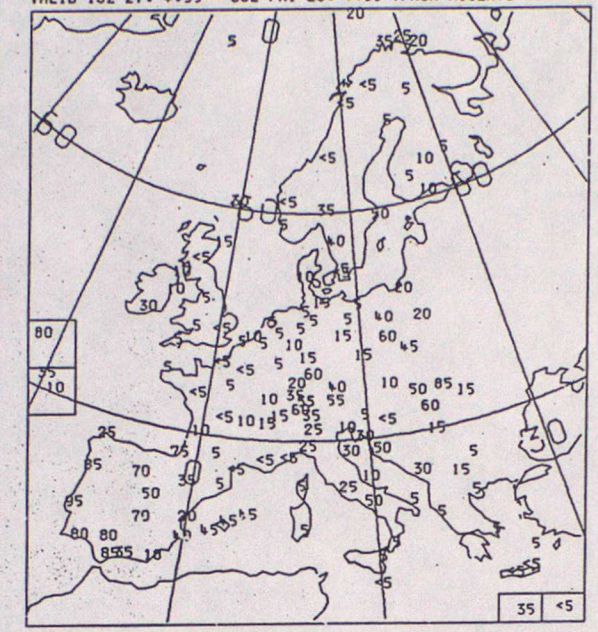
	27 06Z	27 12Z	27 18Z	28 00Z	28 06Z	28 12Z	
002	20	15	30	20	40	30	
005	15	15	25	25	30	25	
006	15	20	35	30	25	25	
008	10	10	10	25	30	25	
017	20	15	25	30	30	30	
022	< 5	5	< 5	< 5	5	5	
026	30	30	30	10	25	25	
031	5	20	30	5	5	15	
034	5	35	15	10	15	30	
044	15	50	50	30	15	40	
047	10	15	15	5	< 5	20	
049	25	25	20	30	35	25	
062	10	15	30	15	10	20	
063	25	20	20	20	10	15	
066	15	20	20	15	15	15	
068	15	15	15	10	10	15	
075	10	25	30	15	30	30	
080	15	35	15	10	5	10	
088	10	5	5	5	< 5	< 5	
091	30	40	15	15	5	15	
100	< 5	< 5	< 5	< 5	< 5	5	
102	< 5	< 5	< 5	5	10	10	
111	< 5	< 5	< 5	< 5	10	5	
132	< 5	5	< 5	5	15	10	
140	< 5	< 5	< 5	< 5	< 5	< 5	
144	< 5	< 5	< 5	< 5	< 5	10	
153	5	5	< 5	< 5	15	10	
155	5	5	< 5	5	10	5	
158	10	15	< 5	< 5	5	5	
160	5	10	< 5	5	10	< 5	
162	5	< 5	< 5	< 5	5	10	
171	< 5	< 5	< 5	10	5	< 5	
204	< 5	< 5	< 5	10	20	10	
210	< 5	5	< 5	< 5	20	10	
212	< 5	5	< 5	< 5	10	5	
214	5	< 5	< 5	< 5	20	5	
215	< 5	< 5	< 5	< 5	< 5	< 5	
220	< 5	5	< 5	< 5	10	10	
224	< 5	< 5	< 5	< 5	< 5	10	
225	< 5	5	< 5	< 5	< 5	10	etc.

PROBABILITY OF PRECIPITATION (GE 0.4MM) FORECASTS.
UKMO UPDATEABLE MOS FORECASTS
FROM THE GLOBAL MODEL RUN AT 00Z 27, APRIL 1995

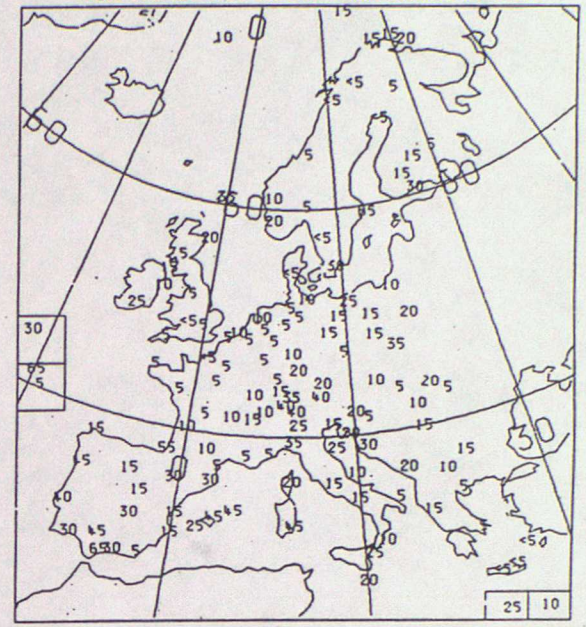
VALID THU 27. 4.95 06Z-18Z (FROM ASCENTS AT T+12)



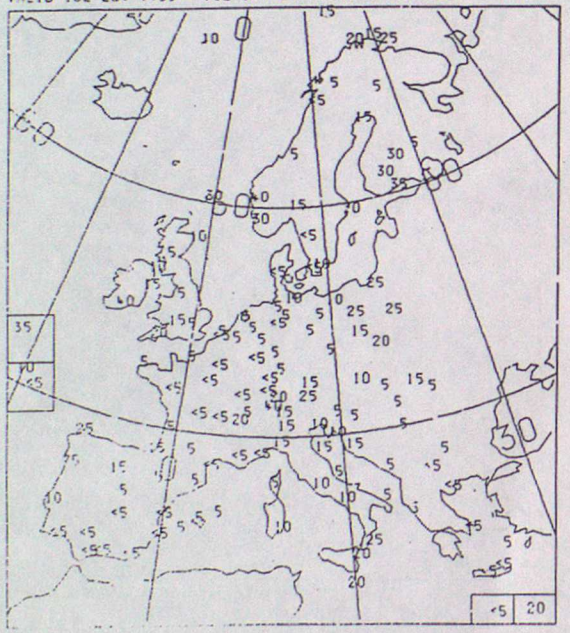
VALID 18Z 27. 4.95 - 06Z FRI 28. 4.95 (FROM ASCENTS AT T+24)



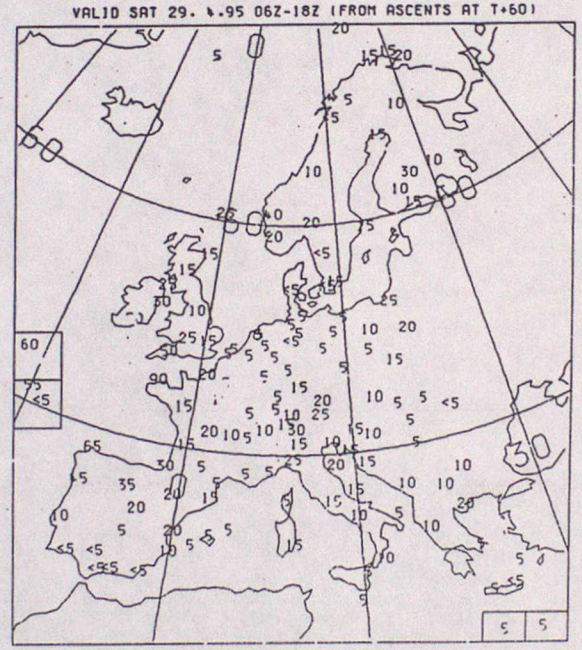
VALID FRI 28. 4.95 06Z-18Z (FROM ASCENTS AT T+36)



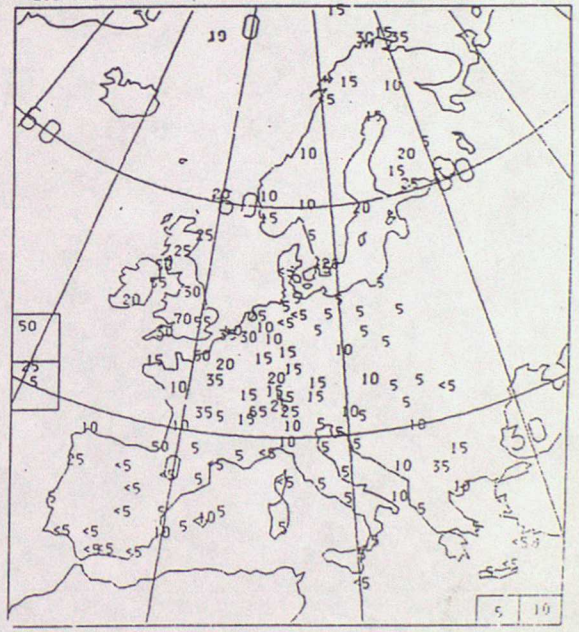
VALID 18Z 28. 4.95 - 06Z SAT 29. 4.95 (FROM ASCENTS AT T+48)



VALID SAT 29. 4.95 06Z-18Z (FROM ASCENTS AT T+60)

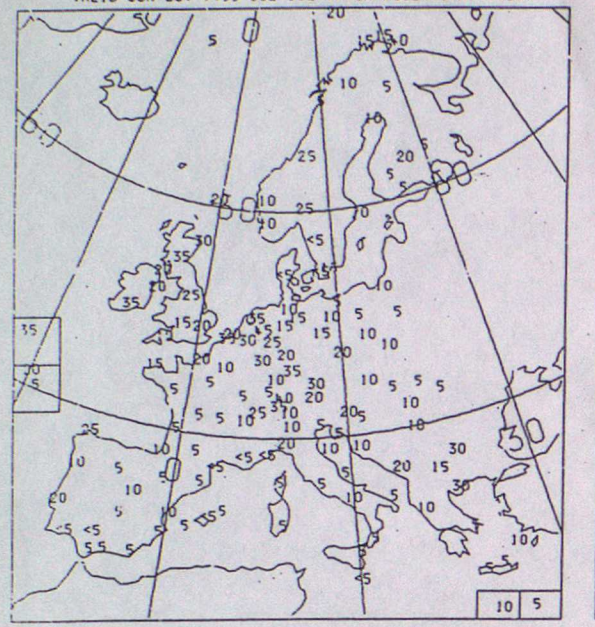


VALID 18Z 29. 4.95 - 06Z SUN 30. 4.95 (FROM ASCENTS AT T+72)

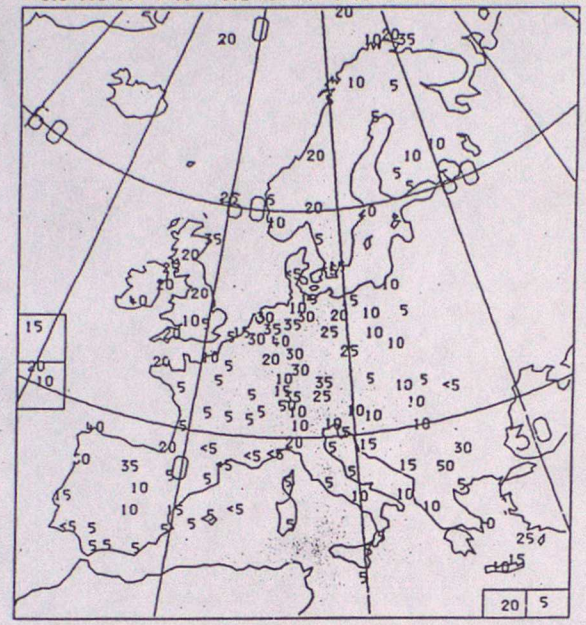


PROBABILITY OF PRECIPITATION (GE 0.4MM) FORECASTS.
UKMO UPDATEABLE MOS FORECASTS
FROM THE GLOBAL MODEL RUN AT 00Z 27, APRIL 1995

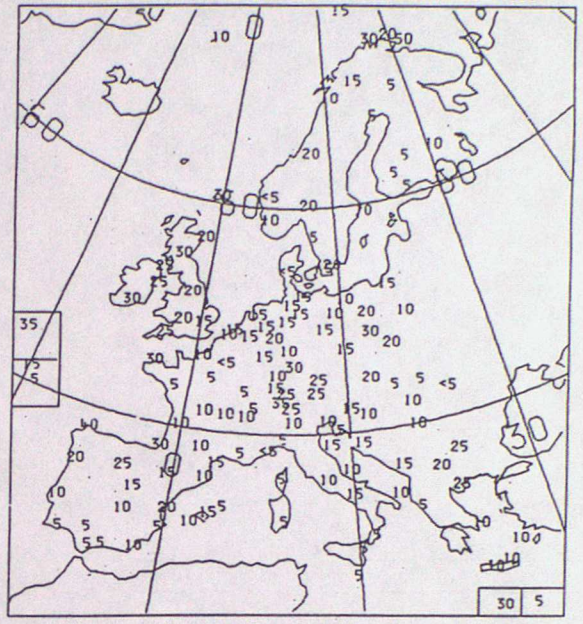
VALID SUN 30. 4.95 06Z-18Z (FROM ASCENTS AT T+84)



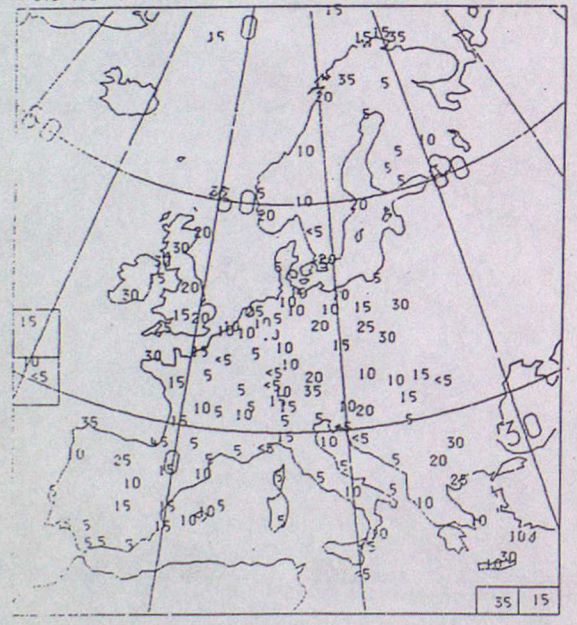
VALID 18Z 30. 4.95 - 06Z MON 1. 5.95 (FROM ASCENTS AT T+96)



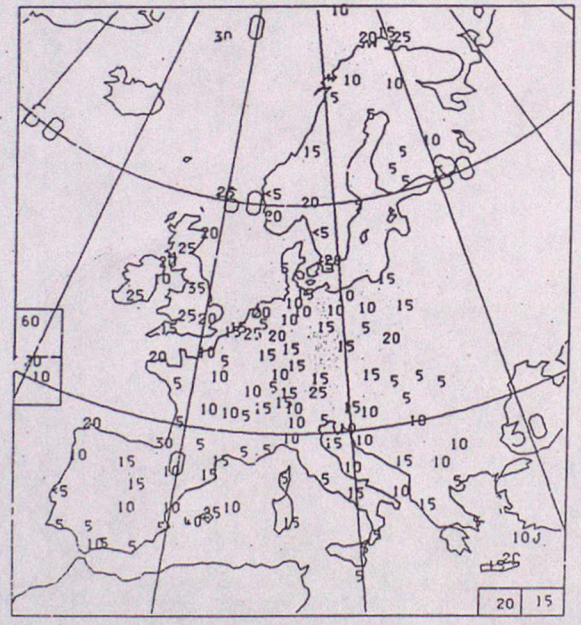
VALID MON 1. 5.95 06Z-18Z (FROM ASCENTS AT T+108)



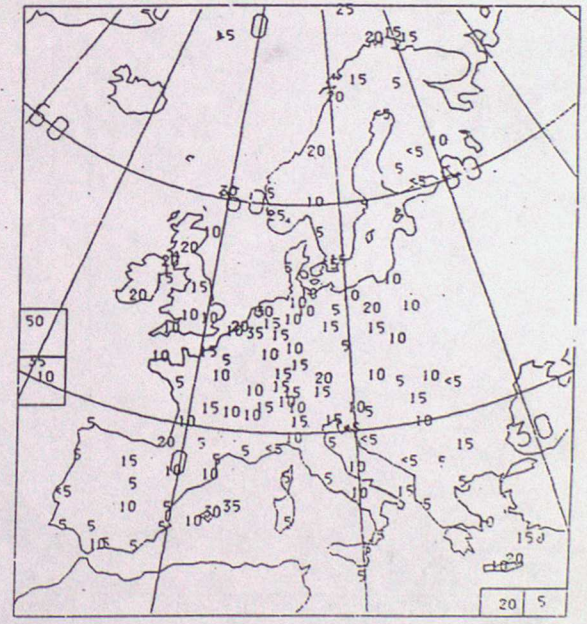
VALID 18Z 1. 5.95 - 06Z TUE 2. 5.95 (FROM ASCENTS AT T+120)



VALID TUE 2. 5.95 06Z-18Z (FROM ASCENTS AT T+132)



VALID 18Z 2. 5.95 - 06Z WED 3. 5.95 (FROM ASCENTS AT T+144)



CENTRAL FORECASTING TECHNICAL NOTE

NUMBER	TITLE	AUTHOR	DATE
2	A trial of a scheme to correct the analysed position of tropical cyclones in the operational coarse mesh model.	M. Carter	1988
3	The impact of data on fine mesh forecasts for the storm of January 25 1990.	J. T. Heming	1990
4	Trial of the impact of bogus data in the fine mesh model.	J. T. Heming	1990
5	A guide to numerical weather prediction models and their output.	C. D. Hall	1991
6	Results of the trial of the scheme to reposition features in a model analysis by use of bogus data.	J. T. Heming	1992
7	Operational forecasts of tropical cyclone formation in the western north pacific in 1991.	C. D. Hall	1992
8	Aviation climatology derived from the opeational model. May 1983 - May 1991	P. M. Grimes	1992
9	Effectivness of grib packing for wafs	H. H. Ross P. J. Smith S. D. Turner	1993
10	Investigation into the impact of North Atlantic tempships on the forecasts of U.K. Meteorological office's global & Limited area models	J. T. Heming A. M. Radford	1993
11	User documentation for the Frontier program.	P. Sinclair	1992
12	A trial of the impact of intervention in the Global Model.	J. T. Heming	1993
13	On the use of gridded binary code in producing aviation forecast bulletins	P. J. Smith S. D. Turner	1987 1993
14	The use of gridded binary code in producing products from Bracknell for international exchange in FM92-IX GRIB	P. J. Smith S. D. turner (Edition 1).	1993
15	Analysis of tropical cyclone forecast errors	S. Coulter	1994
16	Monitoring wind observations from the Capel Dewi MST Radar.	A. M. Radford	1994
17	Report on forecasting the probability of NO_2 air quality events using model output statistics.	C. Strudwicke	1994

CENTRAL FORECASTING TECHNICAL NOTE

NUMBER	TITLE	AUTHOR	DATE
18	Examination of bogus and supported observational data in the operational suite.	S. Waters	1994
19	Subjective assessment of the 'Ambiguity Removal Confidence' for scatterometer winds derived from ERS-1.	S. Waters	1994
20	Results from a parallel trial to investigate the use of satellite cloud motion winds.	A. M. Radford	1994
21	Anomaly correlation coefficients for the global model.	C. Dunlop	1994
22	A trial of a new technique for the bogussing of tropical cyclones.	J. T. Heming	1994
23	Probability of precipitation using updateable model output statistics.	P. M. Grimes G. H. Ross C. C. Strudwicke	1995